“What am I looking for?”

Decoding the neural signal of uncertainty in template matching during visual search

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Introduction

Computational problem:

Visual search can be characterized by the *number of potential search targets:*
→ How to find an *uncertain* target through pattern matching (i.e. through comparing *target representations* vs. *sensory input*)?

Proposed underlying neural dynamics:

- Biased Competition Model of visual attention [1]: maintenance of attentional templates in WM → increased responsivity of a subset of feature-sensitive neurons in visual system
- Candidate mechanism for template matching in WM: fronto-parietal information transfer by theta-gamma synchronization [2; 3]

Research question:

Is *uncertainty* in WM pattern matching reflected by the EEG signal? If so, how? [4]

Discussion

Summary:

- Information about uncertainty in WM pattern matching **is reflected** in the preprocessed EEG activation pattern + ***frontal*** and ***parieto-occipital*** electrodes are the most informative for linear decoding of this information (cf. [2]) ✓✓
- Instantaneous theta-gamma phase-differences ($\Delta\Phi$) did not contain linearly decodable information about any of the factors. They probably varied across trials – which rendered them uninterpretable. ✗

Prospects:

Spatiotemporal decoding of uncertainty using Γ_Φ instead of $\Delta\Phi$:
(1) classical phase synchronization indices for small time bins, or
(2) “synchronization timeseries” with the use of a sliding-window

Results

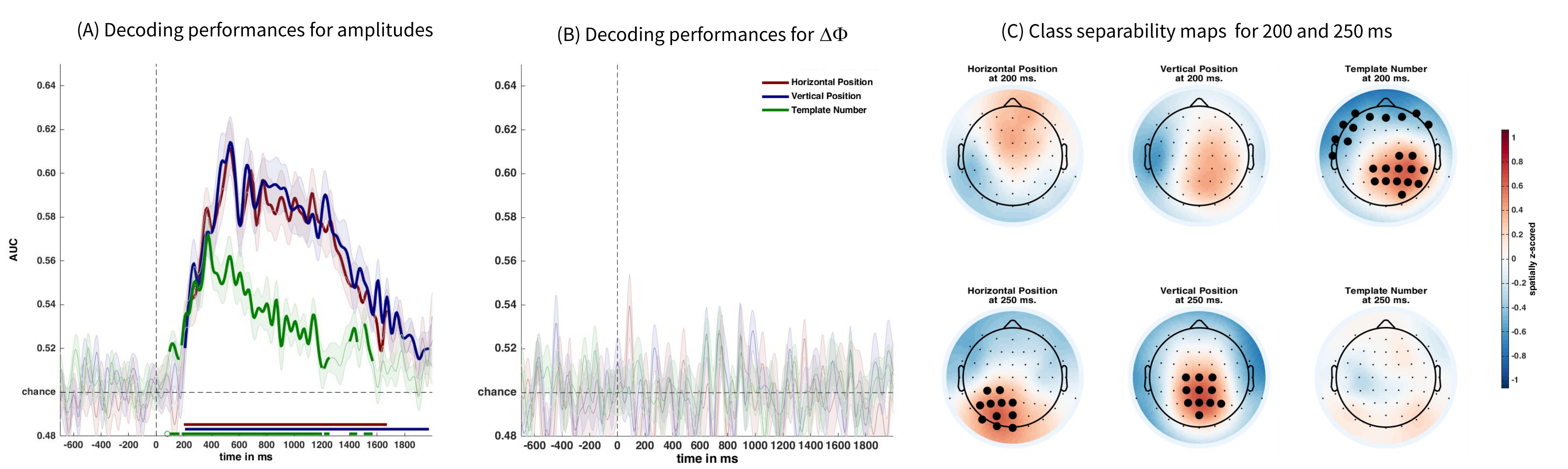


Figure 3 | (A) Amplitude-based mean decoding AUC of Horizontal Position, Vertical Position and Template Number over time. Line graphs are average ± SE in light colors; thick lines reflect $p < 0.05$, cluster-based permutation test. A low-pass filter of 30 Hz was used to smoothen the line graph; (B) Same as (A) but for theta-gamma phase-differences; (C) Activation maps (= correlation / class separability maps) for all factors, reflecting the underlying neural sources for decoding AUC at 200 and 250 ms post-stimulus. Separability is *z*-scored in an interval of -1 and 1. Thick dots reflect channels with $p < 0.05$, cluster-based permutation test.

Methods

Paradigm:

- 35 young adults, learn a set of 4 abstract target symbols: $T = \{t_1, \ldots, t_4\}$
- Uncertainty → size of target subset per block: e.g. $|T_{1,2}| = 1$ vs. $|T_{3,4}| = 3$; $|T_{1,2}| \cap |T_{3,4}| = \emptyset$
- Visual search task: 4 blocks of 48 trials, target subset declared in the beginning of each block

Exemplary trial procedure [4]

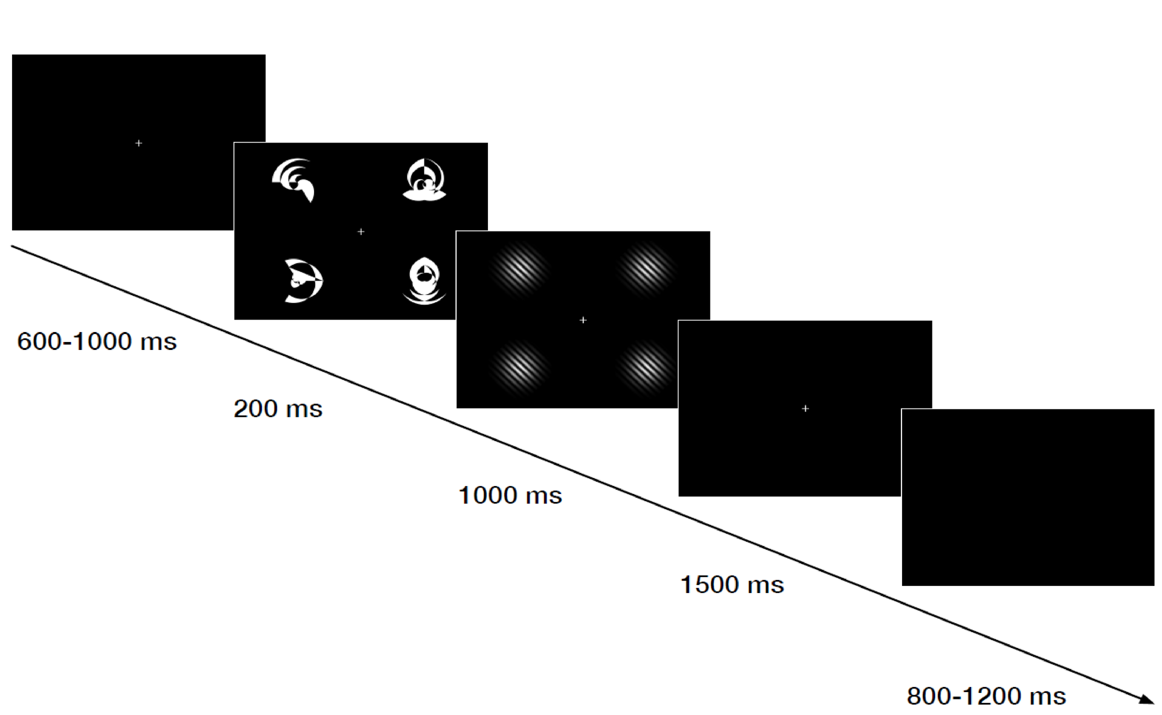


Figure 1 | Task: Keep visual display in WM, match the presented abstract symbols with attentional template, indicate the position (quadrant) of target by button press

EEG protocol:

- *Recording*: 10-10 system + EOG, 1 kHz sampling rate, online notch filter at 50 Hz
- *Preprocessing*: 100 Hz bandpass filter (48 dB/oct), downsampling to 250 Hz, z-value-based automatic artifact rejection and correction with FASTER toolbox [5]
- *Time-frequency analysis*: Complex Morlet wavelets (5 cycles, 6, 30 and 40 Hz center frequencies) + calculation of instantaneous m:n phase-phase differences $\Delta\Phi$ as a precursor to the m:n phase synchronization index Γ_Φ (cf. [6])

Multivariate pattern classification:

- Classes: Template number (1 vs. 3), horizontal position (left vs. right), vertical position (top vs. down) of target
- ADAM Toolbox [7]: Spatiotemporal decoding ([8], cf. Fig. 2) of classes (ceteris paribus) with LDA separately for (1) *amplitude timeseries* and (2) *phase-difference timeseries*, 10-fold cross-validation, shrinkage transformation in each fold
- Additionally: Class separability maps for identification of information-richest channels

Calculation of phase differences [6]

$$\frac{m+n}{2\cdot n}\cdot f_n = \frac{n+m}{2\cdot m}\cdot f_m$$

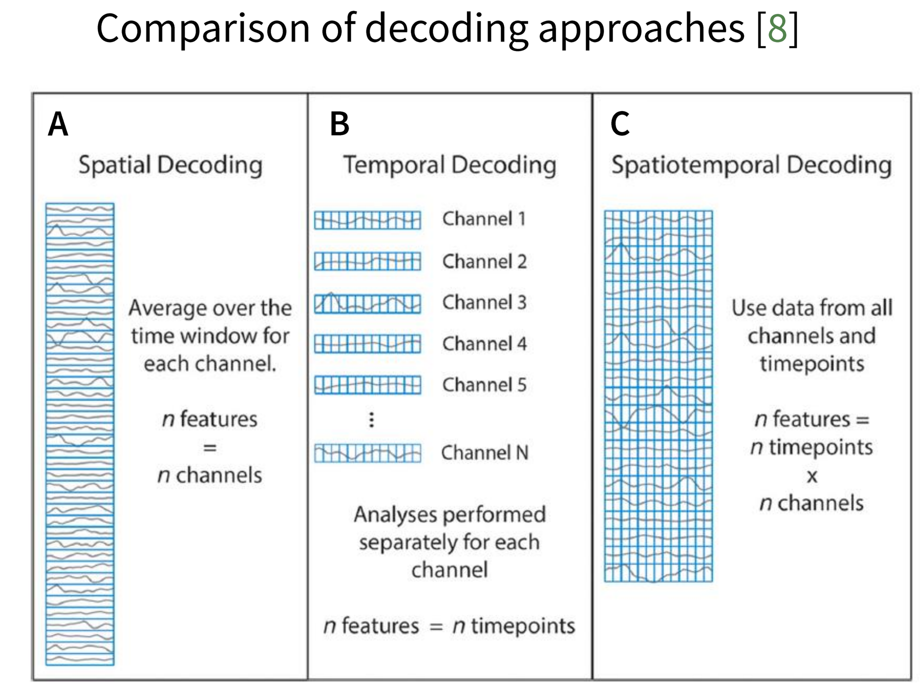
$$\Delta\Phi_k(f_n, f_m, t) \cong \left(\frac{n+m}{2\cdot m}\Phi_1^k(f_m, t) - \frac{m+n}{2\cdot n}\cdot\Phi_2^k(f_n, f)\right) \text{modulus } 2\pi$$

$$\hat{\Gamma}_\Phi(f_n, f_m, t) = |\langle e^{j\cdot\Delta\Phi_k(f_n, f_m, t)}\rangle| \quad , j = \sqrt{-1}$$

Formulae | Generalized phase difference $\Delta\Phi$ and phase synchronization index Γ_Φ for frequencies f_n and f_m of one or two signal components of the *k*-th trial. Note that Γ_Φ yields the *consistency* of the phase difference between two frequencies over a given trial and is therefore not usable for spatiotemporal dedocing!

Figure 2 | (A) Channel-wise timeseries averages are used as features per trial; (B) Instantaneous values of *one* designated channel are used as features per trial; (C) All timepoints at all channels are used in combination as features per trial

Comparison of decoding approaches [8]



Refs.
[1] Desimone & Duncan (1995). *Annu. Rev. Neurosci.*; [2] Sauseng & Klimesch (2008). *Neurosci. Biobehav. Revs.*; [3] Sauseng, Conci, Wild, & Geyer (2015). *Front. Psychol.*; [4] Biel (2016). *Master thesis.*; [5] Nolan, Whelan, & Reilly (2010). *J. Neurosci. Methods*; [6] Sauseng et al. (2008). *NeuroImage*; [7] Fahrenfort et al. (2018). *Front. Neurosci.*; [8] Bode et al. (2019). *Neuroinformatics*.

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